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Abstract: *This paper uses a unique data set to examine the possibility of a structural change in contemporaneous volume–return relation on the Istanbul Stock Exchange (ISE) during the Russian crisis in 1998. The comparison of the relationship during the crisis period to those during pre- and post-crisis periods shows that there was a structural change regarding the price impact of trading volume. The evidence indicates that traders needed to give considerably larger price concessions during the crisis period. The structural change was transitory since the cost of getting liquidity is shown to fall back during the post-crisis period. This study also provides the first evidence on univariate and joint characteristics of fifteen-minute common stock trading volume and returns on the ISE. Both average volume and return show significant univariate intraday variations, and there exists a positive contemporaneous relation between these variables. Moreover, there is weak evidence that in a GARCH setting volume has an impact on conditional return volatility.*

Key words: *GARCH, impact of trading, structural change.*

The Russian Federation is one of the most important trade partners of Turkey. With respect to exports, Russia ranked third and second during 1996 and 1997, respectively. Following the emerging market crisis, which started in October 1997, financial markets crashed in Russia. Russia's fiscal performance was poor, particularly with regard to tax collection. Moreover, little success in privatization efforts, a sharp fall in the price of oil and metals (two-thirds of Russia's exports are commodity-related), and heavy reliance on foreign financing exacerbated the crisis. During 1998, yields on ruble securities shot up to unprecedented levels in mid-May and again in mid-August. On August 17, the Russian central bank announced that it would tolerate a 33 percent drop in the ruble's buying power. In addition,

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Russia postponed payment on government Treasury bills and imposed a 90-day moratorium on payments of foreign debt.

A global financial crisis and, more importantly, the Russian crisis, also hit the Turkish economy. The effects of the crisis were especially felt after the second half of 1998. The gross national product (GNP) growth rate, which was 8.3 percent in 1997, dropped to 2.6 percent in the third quarter, continued to shrink in the last quarter by a mere 0.6 percent, and finalized at 3.9 percent for the year. Turkish exports to and imports from Russia were almost at the $2 billion level in 1997. Exports to this country decreased considerably in 1998 by 34.4 percent, although there was no significant change in imports. Undoubtedly, the economic crisis experienced in this country influenced this steep fall in exports.

As Figure 1 shows, the ISE100 index saw a big drop that coincided with the deepening of the Russian crisis. During the crisis, international investors withdrew their capital from risky countries and looked for more secure investments. The purpose of this paper is to use this period of crisis as a natural experiment and test a view stated in the popular press that the ISE performed well during this period regarding the provision of liquidity to international investors. More specifically, the empirical question is whether the ISE behaved as an orderly market during the crisis period. To test this question, the possibility of a structural change in the contemporaneous relation between trading volume and return is examined by using high frequency data. To give further insight on the bivariate relationship between these two variables, evidence is provided regarding the impact of volume on conditional return variance separately for normal and crisis periods.

The results indicate that there was a structural change regarding the price impact of trading. The price of getting liquidity increased considerably during the crisis and fell back during the post-crisis period. Moreover, there is weak support for the hypothesis that volume has an impact on conditional return variance. In the sample, this impact exists during the noncrisis periods only.

The interaction between trading volume and price change has been an issue for almost forty years (Granger and Morgenstern 1963). As pointed out in a survey article by Karpoff (1987), one benefit of investigating this relationship is the insight gained about the structure of financial markets. Relevant factors noted in the literature include the flow of information, its dissemination, the extent to which prices reflect information, and the effect of market frictions such as the cost of taking a short position.

Empirical research has identified at least two characteristics of the price–volume relationship.[1] Trading volume is positively correlated with both price change and its absolute value. Moreover, the ratio of volume to price change for upticks exceeds the absolute value of the same ratio for downticks. To explain this difference, Karpoff (1987) argues that if the true relationship between the two variables is asymmetric, then incorrect specifications that force a functional or monotonic relation between them can lead to these somewhat inconsistent findings for upticks and downticks. Asymmetry has been confirmed in stock and bond markets, which

Figure 1. **Index Price Level Over Time**

Karpoff believes can be a consequence of the extra cost involved in taking a short position. His explanation is supported by Foster (1995), who reports a symmetric relationship in crude oil futures markets where there is no difference in the cost of long and short positions.

In the literature, volume has also been used to explain time-series properties of financial asset returns. Two of the empirical regularities regarding return are heteroskedasticity and volatility clustering. These features of return volatility are argued to be a reflection of its positive relation to the information arrival rate. This relation is suggested by the mixture of distributions hypothesis (MDH), which states that returns are generated by a mixture of distributions in which the rate of information arrival is the mixing variable. Thus, volume being a proxy for the mixing variable can explain time-series properties of the return.

Modeling time-varying volatility started with Engle's (1982) autoregressive conditional heteroskedasticity (ARCH) process. This specification and its extensions rely on the volatility-clustering feature of returns. However, if MDH holds, explanatory variables in ARCH-type models would lose their explanatory power when information arrival rate (or its proxy, volume) is added into the conditional return variance equation. To sum up, if MDH holds, the use of the time variability of volume will be sufficient to explain the time variability of return volatility. Moreover, volatility clustering will be a reflection of serial correlation in volume time series. Both Lamoureux and Lastrapes (1990a) and Najand and Yung (1991) report that volume has significant explanatory power regarding return volatility, although the strengths of the evidence in these two studies differ.

The Data

The ISE is a fully automated, continuous auction market that matches buy and sell orders on a price and time priority basis. The first transaction on the ISE was executed on January 3, 1986.[2] Full automation of trading occurred on October 21, 1994. This is a rapidly growing market, as revealed by various measures of total trading activity. During the 1994–1998 period, annual dollar volume tripled, share volume increased more than twentyfold, and the number of contracts quadrupled.

One notable feature of the ISE is the extent of foreign investment in it, which has more than tripled since December 1995. At the beginning of 1998, about half the floating equity in this market was owned by foreigners. This feature is especially important for this study since the level of portfolio holdings of international investors in emerging markets are highly sensitive to a change in risk in these markets. These investors tend to leave emerging stock markets quickly during crisis periods. Such an action is likely to put these relatively thin markets into a challenge regarding liquidity provision.

The sample used in this study consists of thirty stocks that made up the ISE30 index as of February 26, 1999. These are the most actively traded stocks on the ISE. The sample period covers fourteen months, from January 1998 through February 1999. The data were provided by the ISE. It includes transaction number, time, session, day, price, and size variables.

Table 1 shows some characteristics of the sample. The median firm has been listed for about seven-and-a-half years. It has a market value of $467 million. The last column shows the fraction of shares kept in the ISE Settlement and Custody Bank, which is a proxy of the fraction of shares held by the public. The median float rate is 20 percent—a low figure. There are two reasons for that. First, most of the firms are controlled by families, as in Italy and some other countries. For example, nine of the thirty firms (Arçelik, Koç Holding, Migros, Otosan, Türk Otomobil Fab., Akbank, Akçimento, Aksigorta, and Sabancı Holding) are controlled by the Koç and Sabancı families. Their unwillingness to share control of these companies is likely a reason for the relatively low float rates. Second, some firms (Petkim, Petrol Ofisi, Tüpraş, and Türk Hava Yolları) were completely state-owned enterprises. In the first step of a privatization plan, the state reduced its holdings in these firms. However, it still had majority ownership as of the end of February 1999.

The sample is representative of the entire market. These thirty stocks generated approximately 70 percent of total trading volume during the sample period. Over the same time period, the correlation between the ISE100 index and the equal weighted sample average is 0.976. These figures show that the sample stocks reflect most of the trading and price change activity in the market. The trading in sample stocks covers most of the foreign involvement in Turkish stocks. On average, trading in these stocks constituted 81.65 percent of total monthly foreign volume in 1998.

Table 1

Some Characteristics of ISE Stocks in the Sample

Stock	Industry	Traded since	Market capitalization (million $)	Float (%)
Akbank	Banking	7/26/90	3,496	15
Akçansa	Cement	10/6/87	411	15
Aksigorta	Insurance	12/5/94	273	29
Alarko Holding	Conglomerates	5/24/89	193	23
Alcatel Teletaş	Telecom	3/22/88	123	33
Arçelik	Consumer durables	1/21/86	544	19
Bağfas	Fertilizers and insecticides	1/28/86	83	59
Cukurova Elektrik	Utilities	1/7/86	630	18
Doğan Holding	Conglomerates	6/21/93	363	34
Doğan Yayın Holding	Conglomerates	8/6/98	274	15
Efes Holding	Conglomerates	2/19/98	168	46
Enka Holding	Conglomerates	1/24/86	373	15
Ereğli Demir Çelik	Iron and steel	1/13/86	522	41
Garanti Bankası	Banking	6/6/90	2,007	20
Hürriyet Gazetecilik	Media	2/25/92	320	18
Ihlas Holding	Conglomerates	3/17/94	187	25

Iş Bankası (C)	Banking	11/16/87	5,007	33
Koç Holding	Conglomerates	1/10/86	1,819	13
Migros	Retail	2/27/91	1,327	48
Net Holding	Conglomerates	10/5/89	51	55
Ford Otosan	Automotive	1/13/86	588	15
Petkim	Petroleum products	7/9/90	1,931	4
Petrol Ofisi	Petroleum products	5/30/91	1,337	7
Sabancı Holding	Conglomerates	7/8/97	2,977	12
Türk Hava Yolları	Airlines and services	12/20/90	1,620	2
Tofaş Otomobil Fab.	Automotive	7/1/91	181	22
Tüpraş	Petroleum products	5/30/91	4,865	4
Uzel Makina	Automotive	8/5/97	204	15
Vestel	Consumer durables	6/27/90	377	31
Yapı Kredi Bankası	Banking	5/28/87	2,473	39
Mean			1,157	24
Median		7/3/90	467	20

Source: Istanbul Stock Exchange 2000.

Notes: Column 3 reports the date each stock became listed; column 4 shows the market value of each firm in dollars; column 5 shows the percentage of shares kept in custody by the ISE Settlement Bank. All figures are as of the close of the second trading session on March 12, 1999.

Empirical Analysis

The analysis in this paper is based on clock time by sampling price and volume information every fifteen minutes. There were 283 trading days in the sample period, of which 277 were standard trading days with sixteen fifteen-minute intervals. On the remaining six days, either there was trading only during the first session or there were trading delays/halts. As a result, there are 4,500 intervals during the sample period.

Return and Volume Series

To construct an equally weighted price and volume series, the following procedure was adopted. The use of nominal stock prices would assign larger weights to higher priced stocks. Therefore, the nominal price series are adjusted so that the price of each stock equals 100 at the beginning of the sample period. The final price index relies on these individual stock indices.[3]

The return series is the difference of logarithmic prices at the end of consecutive intervals. Close-to-open returns (both overnight and midday) are excluded to eliminate any possible confounding effects from information that arrives when the market is closed. For most stocks, the number of outstanding shares changed during the sample period, thus trading activity is measured by share turnover. Due to the large cross-sectional variation in the float rate, share turnover is defined as the ratio of shares traded to floating shares.

Formal stationarity tests are performed for price, return, and percentage turnover series. Both the augmented Dickey-Fuller and Phillips-Perron tests give consistent results. The hypothesis that the volume (return) series contains at least one unit root is rejected at the 0.001 level of significance, so it is concluded that this series is stationary. Neither test indicates rejection for the price series. Figures 2 and 3 show the return and turnover over the sample period, respectively.

Intraday and interday variation in stock returns, return volatility, and trading volume have been shown in other markets. Since this is the first study to employ intraday transaction data from the ISE, a univariate analysis of systematic intraday patterns in these three variables is presented before investigating the bivariate relationships.

Time-of-Day and Day-of-the-Week Effects

Intraday Trading Volume

Table 2 shows the average turnover for each interval and each weekday. The overall average turnover during a fifteen-minute interval is 0.467 percent. For each day of the week, turnover attains maximum value during the first interval and it is about twice the amount observed in the remaining intervals. Turnover is also high during the first and last intervals of the second trading session. High trading activity during

Figure 2. **Percentage Turnover Over Time**

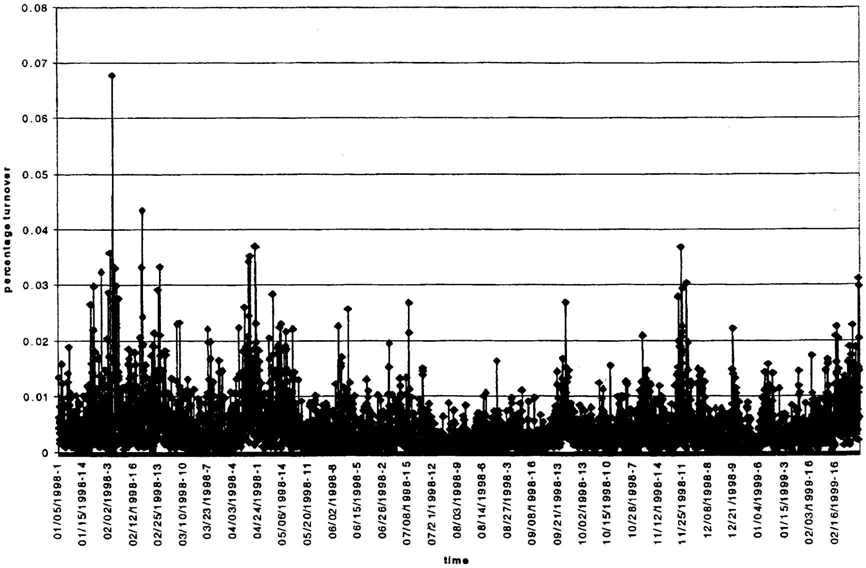

Figure 3. **Index Return Over Time**

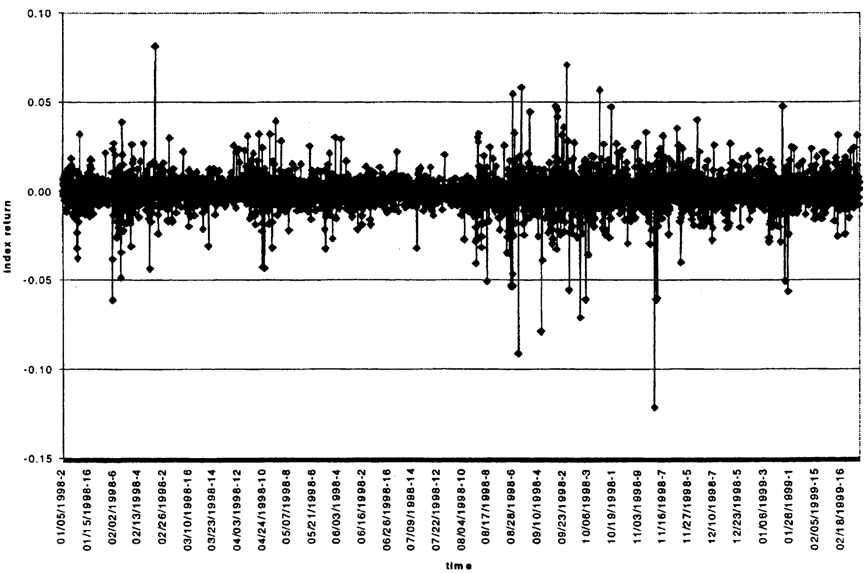

Table 2

Average Turnover During Fifteen-Minute Intervals by Weekday (in percent)

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00–10:15	1.018	0.876	0.986	0.970	0.911	0.952	0.40
10:15–10:30	0.534	0.536	0.636	0.565	0.535	0.561	0.57
10:30–10:45	0.371	0.425	0.414	0.484	0.415	0.422	0.74
10:45–11:00	0.304	0.350	0.368	0.351	0.371	0.349	0.38
11:00–11:15	0.286	0.308	0.338	0.310	0.350	0.318	0.49
11:15–11:30	0.278	0.321	0.311	0.285	0.278	0.295	0.27
11:30–11:45	0.242	0.225	0.379	0.300	0.333	0.295	2.30[b]
11:45–12:00	0.298	0.365	0.351	0.353	0.334	0.340	0.34
14:00–14:15	0.566	0.667	0.634	0.644	0.662	0.634	0.20
14:15–14:30	0.465	0.528	0.469	0.508	0.443	0.483	0.30
14:30–14:45	0.337	0.439	0.376	0.448	0.388	0.398	0.64
14:45–15:00	0.313	0.408	0.367	0.373	0.410	0.374	0.64
15:00–15:15	0.311	0.362	0.441	0.410	0.439	0.392	1.03
15:15–15:30	0.364	0.452	0.389	0.474	0.409	0.418	0.67
15:30–15:45	0.370	0.455	0.444	0.433	0.450	0.430	0.55
15:45–16:00	0.700	0.846	0.862	0.785	0.850	0.809	1.29

All	0.422	0.473	0.485	0.481	0.474	0.467
F_{int}	17.02[a]	8.02[a]	9.94[a]	11.43[a]	11.60[a]	
F_{first}	187.68[a]	61.77[a]	85.89[a]	101.70[a]	96.01[a]	
F_{ninth}	22.44[a]	16.45[a]	14.74[a]	19.59[a]	24.82[a]	
$F_{sixteenth}$	66.69[a]	55.88[a]	61.33[a]	54.33[a]	81.64[a]	

Notes: Turnover per stock is calculated by dividing the cumulative volume during an interval by the number of floating shares (number of outstanding shares * float). The reported results are the equal weighted averages of individual stock mean turnovers. F_{int} tests the hypothesis of equality of mean turnover during all intervals in a given weekday. F_{first}, F_{ninth}, and $F_{sixteenth}$ test the hypotheses that mean turnover in interval 1, 9, and 16 are not different from the mean turnover in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean turnover during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday–Friday, respectively. F_{first}, F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday–Friday, respectively. F_{day} has degrees of freedom of (4,272). [a] Significant at the 1 percent level; [b] Significant at the 10 percent level.

the first interval of both sessions can be attributed to the effect of information flow during the non-trading periods, whereas the increase during the last interval of the day probably reflects the concern of traders to rebalance their holdings before the market closes.

Several analysis of variance tests were performed to measure the variability of mean turnover across intervals and days. Table 2 shows these F-tests. F_{int} tests the hypothesis of equality of mean turnover during all intervals in a given weekday. F_{first} (F_{ninth}, $F_{sixteenth}$) tests the hypothesis that mean turnover in interval 10:00–10:15 (14:00–14:15, 15:45–16:00) is not different from the mean turnover in the remaining intervals (excluding those three intervals). F_{day} tests the hypothesis that there is no interday difference in mean turnover during a given interval. Overall, the results suggest weak interday but strong intraday variation in turnover.

Intraday Volatility

Table 3 shows average return squared for each interval and each weekday. This measure is a proxy for unconditional return volatility during an interval. The volatility of return increases during the first interval of each session, but it is much higher during the first interval of the day. The definition of F_{int}, F_{first}, F_{ninth}, $F_{sixteenth}$, and F_{day} in Table 3 are analogous to the F-tests in Table 2. Combined with the turnover pattern, the variation in volatility suggests that the incorporation of new information into prices occurs during the first interval of both trading sessions, and the high turnover at the end of the day is due to portfolio rebalancing rather than the effect of information.

To complement the picture, Table 4 shows the time-of-day and day-of-the-week effects for average return. Similar to the behavior of the other two series, there seems more intraday than interday variation in average returns. A large positive return during the last interval of the second session is the most striking pattern. This may be caused by buyer-initiated trades to close short positions by the end of the trading day. Positive returns on Friday afternoon and negative returns on Monday suggest that investors prefer to take long positions during the weekend and liquidate their holdings on the first day of the week.

The univariate analysis so far shows systematic temporal patterns in return, volatility, and turnover. The time-of-day rather than day-of-the-week effect seems to be the dominant source. To remove seasonality, the return and turnover series were standardized using time-of-day and day-of-the-week means and standard deviations. The analysis in the remainder of this paper uses these two standardized time series.

Contemporaneous Price–Volume Relationship

To examine the contemporaneous relationship between price change and turnover, a modified version of Jain and Joh's (1988) empirical specification is used. Consistent with the theoretical models of Epps (1975) and Karpoff (1986, 1987),

Table 3

Average Return Volatility During Fifteen-Minute Intervals by Weekday ($\times 10^{-4}$)

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00–10:15	2.737	1.770	2.925	2.155	3.671	2.647	0.67
10:15–10:30	0.982	0.763	0.768	0.798	1.130	0.888	0.33
10:30–10:45	0.541	0.816	0.443	1.070	1.004	0.773	0.69
10:45–11:00	0.420	0.241	0.360	0.382	0.375	0.355	0.52
11:00–11:15	0.420	0.279	0.541	0.311	0.584	0.426	0.61
11:15–11:30	0.535	0.288	0.306	0.239	0.461	0.366	0.66
11:30–11:45	0.332	0.170	0.282	0.284	0.254	0.264	0.54
11:45–12:00	0.356	0.270	0.261	0.297	0.221	0.281	0.58
14:00–14:15	0.922	1.126	0.978	1.358	1.083	1.092	0.31
14:15–14:30	0.385	0.760	0.470	0.409	0.443	0.495	1.13
14:30–14:45	0.373	0.210	0.310	0.620	0.606	0.421	1.67
14:45–15:00	0.183	0.229	0.534	0.204	0.327	0.295	3.33[b]
15:00–15:15	0.279	0.410	0.489	0.400	0.441	0.403	0.42
15:15–15:30	0.396	0.417	0.358	0.357	0.737	0.453	0.75
15:30–15:45	0.502	0.278	0.365	0.406	0.730	0.455	1.05
15:45–16:00	0.334	0.623	0.414	0.295	0.526	0.440	1.50

(continues)

Table 3 (continued)

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
All	0.606	0.541	0.613	0.599	0.787	0.628	
F_{int}	5.58[a]	5.57[a]	4.11[a]	4.86[a]	4.41[a]		
F_{first}	70.09[a]	63.38[a]	52.55[a]	51.77[a]	53.99[a]		
F_{ninth}	9.41[a]	18.20[a]	19.15[a]	21.92[a]	3.48[c]		
$F_{sixteenth}$	0.51	2.27	0.00	0.88	0.02		

Notes: The reported results are the equal weighted averages of individual stock volatilities, proxied by return squared. F_{int} tests the hypothesis of equality of mean volatility during all intervals in a given weekday. F_{first}, F_{ninth}, and $F_{sixteenth}$ test the hypotheses that mean volatility in intervals 1, 9, and 16 are not different than the mean volatility in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean volatility during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday–Friday, respectively. F_{first}, F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday–Friday, respectively. F_{day} has degrees of freedom of (4,272). [a] Significant at the 1 percent level; [b] Significant at the 5 percent level; [c] Significant at the 10 percent level.

Table 4

Average Return During Fifteen-Minute Intervals by Weekday

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
10:00–10:15	–0.245	–0.020	0.017	0.301	0.287	0.065	1.10
10:15–10:30	–0.006	–0.112	0.081	0.139	–0.010	0.017	0.57
10:30–10:45	–0.092	–0.272	0.059	–0.235	–0.137	–0.136	1.25
10:45–11:00	0.027	–0.066	–0.041	–0.108	–0.123	–0.062	0.56
11:00–11:15	0.012	–0.104	–0.170	–0.118	0.002	–0.075	0.82
11:15–11:30	–0.072	–0.010	–0.146	–0.021	–0.119	–0.073	0.54
11:30–11:45	–0.055	–0.025	–0.088	0.055	–0.108	–0.044	0.85
11:45–12:00	0.153	0.066	0.112	–0.052	0.229	0.102	2.23[c]
14:00–14:15	–0.040	0.021	–0.026	–0.052	0.113	0.003	0.22
14:15–14:30	0.016	–0.021	–0.098	0.055	0.065	0.003	0.48
14:30–14:45	0.039	0.040	0.003	–0.050	0.034	0.014	0.19
14:45–15:00	–0.095	0.005	–0.142	–0.125	0.072	–0.057	1.60
15:00–15:15	–0.244	0.018	–0.062	–0.043	0.063	–0.054	1.94
15:15–15:30	–0.029	0.051	–0.122	–0.049	0.176	0.006	1.58
15:30–15:45	–0.052	–0.037	0.075	–0.001	0.085	0.014	0.48
15:45–16:00	0.139	0.473	0.369	0.301	0.455	0.348	3.32[b]

(continues)

Table 4 (continued)

Interval	Monday	Tuesday	Wednesday	Thursday	Friday	All	F_{day}
All	−0.034	0.001	−0.011	0.000	0.068	0.004	
F_{int}	1.09	2.43[a]	1.64[c]	1.92[b]	1.87[b]		
F_{first}	3.98[b]	0.03	0.29	10.55[a]	4.74[b]		
F_{ninth}	0.01	0.39	0.03	0.01	0.78		
$F_{sixteenth}$	3.49[c]	34.78[a]	20.93[a]	13.88[a]	17.89[a]		

Notes: Return per stock is calculated as the difference of log prices at the end and at the beginning of an interval. The reported results are the equal weighted averages of individual stock mean returns. F_{int} tests the hypothesis of equality of mean return during all intervals in a given weekday. F_{first}, F_{ninth}, and $F_{sixteenth}$ test the hypotheses that mean return in intervals 1, 9, and 16 are not different than the mean return in the remaining intervals, respectively (excluding intervals 1, 9, and 16). F_{day} tests the hypothesis that there is no interday difference in mean return during a given interval. F_{int} has degrees of freedom of (15,880), (15,896), (15,864), (15,848), and (15,864) for Monday–Friday, respectively. F_{first}, F_{ninth}, and $F_{sixteenth}$ have degrees of freedom of (1,782), (1,796), (1,768), (1,754), and (1,768) for Monday–Friday, respectively. F_{day} has degrees of freedom of (4,272).
[a] Significant at the 1 percent level; [b] significant at the 5 percent level; [c] significant at the 10 percent level.

which predict an asymmetric relationship, Equation (1) allows for the relation to be different for positive and nonpositive returns.

$$\begin{aligned}\text{Volume}_t = a + b \cdot \text{Period}_t + c \cdot \left|\text{Return}_t\right| + d \cdot \text{Period}_t \cdot \left|\text{Return}_t\right| \\ + e \cdot \text{Neg}_t \cdot \left|\text{Return}_t\right| + f \cdot \text{Period}_t \cdot \text{Neg}_t \cdot \left|\text{Return}_t\right|,\end{aligned} \tag{1}$$

where Period is a dummy variable that equals one during a specified period, zero otherwise; and Neg is a dummy variable that takes on the value of one when return is negative, zero otherwise. The dummy variable Period is used to distinguish different time intervals during the sample period. The interval January 1, 1998 to July 31, 1998 is classified as the pre-crisis period, whereas the August 1, 1998 to October 24, 1998 and October 25, 1998 to February 29, 1999 time frames are classified as crisis and post-crisis periods, respectively. The above specification is estimated three times with the purpose of testing the following hypothesis.[4]

> H_0: The price concession required to initiate a trade is larger during a crisis period than that during normal periods.

Relation Between Return Volatility and Volume

Engle's (1982) ARCH model and its extension, the generalized ARCH (GARCH) model by Bollerslev (1986), have found wide application in the literature. In his survey article, Palm (1996) motivates GARCH models of volatility as having been developed to account for empirical regularities of financial data. Some of these regularities regarding financial asset returns are little or no autocorrelation, time-varying conditional variance, and rejection of normality in favor of some tick-tailed distribution.

To examine the relationship between conditional return variance and the trading volume, the GARCH(1,1) model is used in this study.

$$\begin{aligned}\text{Return}_t &= \mu_t + \varepsilon_t \\ \varepsilon_t \left| \varphi_{t-1} \right. &\sim N\left(0, h_t\right) \\ h_t &= \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1},\end{aligned} \tag{2}$$

where φ_{t-1} shows the information set at time $t-1$, and h_t denotes conditional return variance at time t. Bollerslev (1987) shows that this parsimonious specification provides an appropriate fit for many financial time series.[5] The impact of volume on return volatility is examined by adding volume into the conditional variance equation of GARCH(1,1) in Equation (2).

Findings

Table 5 reports the coefficients and their p-values from the estimation of the model in Equation (1) by using standardized return and turnover series. To account for

Table 5

Contemporaneous Price–Volume Relationship

Case	Comparison	Period = 1 if	*a*	*b*	*c*	*d*	*e*	*f*
1	Pre to crisis	Pre	−0.5997	0.2877	0.3310	0.4374	−0.0737	−0.0059
			(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	(0.0214)	(0.9346)
2	Crisis to post	Post	−0.5997	0.2392	0.3310	0.2056	−0.0737	0.0637
			(<0.0001)	(<0.0001)	(<0.0001)	(0.0019)	(0.0215)	(0.3651)
3	Pre to post	Post	−0.3120	−0.0486	0.7684	−0.2318	−0.0796	0.0696
			(<0.0001)	(0.3612)	(<0.0001)	(0.0036)	(0.2150)	(0.4388)

Notes: The following model is estimated in each case by using standardized return and volume series:

$$\text{Volume}_t = a + b \cdot \text{Period}_t + c \cdot |\text{Return}_t| + d \cdot \text{Period}_t \cdot |\text{Return}_t|$$
$$+\, e \cdot \text{Neg}_t \cdot |\text{Return}_t| + f \cdot \text{Period}_t \cdot \text{Neg}_t \cdot |\text{Return}_t|,$$

where Period is a dummy variable that equals one during a period, zero otherwise; Neg is a dummy variable that takes on the value of one when return is negative, zero otherwise.

The table reports the estimated coefficients and their *p*-values in parentheses. To account for heteroskedasticity and autocorrelation in disturbance terms, in each case the model is estimated with the Newey and West (1987) approach.

heteroskedasticity and autocorrelation in disturbance terms, in each case, the model is estimated with the Newey and West (1987) approach.[6]

The first set of coefficients, *a, c,* and *e,* represent the intercept, the slope of the volume–return relation, and the extent of asymmetry in this relation, respectively. The second set, *b, d,* and *f,* show the effect of using a different estimation period on the first set of coefficients, respectively.

The first case compares pre-crisis and crisis periods. As has been shown for other exchanges, coefficient *c* indicates a positive relation between volume and absolute value of return. The asymmetry as measured by the coefficient *e* is consistent with the Epps (1975) and Karpoff (1986, 1987) models. Coefficient *d* shows the effect of estimation period on the volume–return relation. Its positive sign indicates a larger price impact of trading during the crisis period than during the pre-crisis period. Moreover, the positive *b* coefficient suggests, irrespective of size, trading during the crisis period is associated with a larger change in absolute return than trading during the pre-crisis period.

The second case compares crisis and post-crisis periods. Coefficients *b* and *d* are both positive but smaller than those in the first case. This finding indicates that price impact of trading decreases after the crisis period. However, the fall is not big enough to bring it back to the pre-crisis level.

This conclusion is confirmed by the coefficient estimates for the third case, where only coefficient *d* from the second set is significant. Therefore, given the above specification the structural change that occurred during the crisis period was partially reversed during the post-crisis period. It seems likely that, if the post-crisis period could be extended beyond the end of the sample period, price impact of trading may be observed to fall back to the pre-crisis level.

Overall, these findings provide strong support for the hypothesis that gaining liquidity is considerably more expensive during a crisis period than it is during a normal period.

Table 6 contains descriptive sample statistics on the distribution of standardized return and volume series during the three subperiods in the sample. The evidence about return distribution indicates significantly fatter tails than does the stationary normal distribution for all the subperiods. The distribution is not symmetric in pre- and post-crisis periods. Kiefer-Salmon (K and S) statistics (Keifer and Salmon 1983) show how much of nonnormality can be attributed to excess kurtosis and nonsymmetry of the distribution in each case. For all the subperiods, excess kurtosis is more prominent than skewness in the sample. This evidence suggests the appropriateness of GARCH modeling, which is consistent with leptokurtosis. Table 6 also displays persistence in trading volume. The Ljung-Box Q(3) statistic (Ljung and Box 1978) for the cumulative effect of up to third-order autocorrelation in the standardized volume exceeds the 5 percentile critical value of 7.81 for all subperiods. This evidence is consistent with the assumption of persistence in the rate of information arrival given volume serves as a good proxy for it.

Table 6

Sample Statistics for Standardized Return and Volume During the Three Subperiods

	Pre	Crisis	Post
N	2240	944	1248
Return			
Mean	–0.0033	–0.0605	0.0516
Std	0.8415	1.3256	0.9673
S[a]	72.89	0.60	8.37
K[a]	893.36	4013.46	89.82
S+K[b]	966.25	4014.06	98.19
D(p)	<0.0100	<0.0100	<0.0100
Max	4.1297	6.7412	3.5624
Q3	0.4504	0.6620	0.6338
Median	0.0287	–0.0726	0.0367
Q1	–0.3913	–0.7660	–0.4969
Min	–6.2552	–5.8016	–4.9652
Volume			
Q(3)[c]	562.5	329.5	547.05

Notes: [a] Under the null, distributed as $\chi(1)$. Five percent critical value is 3.84. [b] Under the null, distributed as $\chi(2)$. Five percent critical value is 5.99. [c] Under the null, distributed as $\chi(3)$. Five percent critical value is 7.81.

S(K) is the Kiefer-Salmon statistic testing the null hypothesis of normality against the alternative of skewness (excess kurtosis). S+K is the joint Kiefer-Salmon statistic for normality; the alternative is skewness or excess kurtosis. D(p) is the *p*-value of the Kolmogorov-Smirnov statistic. Q(3) is the Ljung-Box statistic for autocorrelations up to three lags.

Table 7 shows the coefficient estimates of GARCH(1,1) for the three subperiods. Panel A shows the results without volume. The Ljung-Box Q(3) statistic for adjusted residuals, $\varepsilon_t h_t^{-1/2}$ indicates that the GARCH(1,1) specification provides a good fit for the pre- and post-crisis, but not for the crisis period. One possible explanation for this result may be the considerable increase in leptokurtosis during the crisis period, as shown in Table 6. Panel B of Table 7 shows the results when volume is added into the conditional variance equation. For the two periods in which the GARCH specification is shown to provide an adequate fit, volume is significant and GARCH effects decrease considerably with the inclusion of volume. The use of contemporaneous volume in the conditional variance equation may be objectionable due to the potential simultaneity problem—that is, return

Table 7

Maximum Likelihood Estimates of GARCH(1,1) Model

	μ	α_0	α_1	α_2	α_3	Q(3)[a]
Panel A						
Pre	0.0029	0.0350	0.1009	0.8492	—	1.26
	(0.8531)	(<0.0001)	(<0.0001)	(<0.0001)		
Crisis	–0.0679	0.0311	0.1030	0.8818	—	24.24
	(0.0656)	(0.0001)	(<0.0001)	(<0.0001)		
Post	0.0648	0.0363	0.0681	0.8939	—	4.99
	(0.0145)	(0.0006)	(<0.0001)	(<0.0001)		
Panel B						
Pre	–0.0015	0.5042	0.1010	0.0000	0.2713	1.64
	(0.9244)	(<0.0001)	(<0.0001)	(1.0000)	(<0.0001)	
Crisis	–0.0752	1.7252	0.1537	0.0000	1.3424	15.19
	(0.0150)	(<0.0001)	(0.0001)	(1.0000)	(<0.0001)	
Post	0.0486	0.8211	0.1069	0.0000	0.6512	3.33
	(0.0274)	(<0.0001)	(0.0004)	(1.0000)	(<0.0001)	
Panel C						
Pre	0.0056	0.0437	0.0883	0.8445	0.0206	1.43
	(0.7285)	(<0.0001)	(<0.0001)	(<0.0001)	(<0.0001)	
Crisis	–0.0679	0.0311	0.1030	0.8818	0.0000	24.24
	(0.0656)	(0.0001)	(<0.0001)	(<0.0001)	(1.0000)	
Post	0.0663	0.0439	0.0614	0.8920	0.0142	4.72
	(0.0127)	(0.0003)	(<0.0001)	(<0.0001)	(0.0659)	

Notes: The following model is estimated in each case by using standardized return and volume series:

$$\text{Return}_t = \mu_t + \varepsilon_t$$

$$\varepsilon_t \left| \varphi_{t-1} \sim \mathrm{N}(0, h_t) \right.$$

$$h_t = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 h_{t-1} + \alpha_3 \mathrm{vol}_t,$$

where φ_{t-1} shows the information set at time $t-1$ and h_t denotes conditional return variance at time t.

Panel A estimates the model by imposing $\alpha_3 = 0$ restriction. The unrestricted model estimation results are reported in Panel B. Panel C shows the unrestricted model estimation results, where vol_t is replaced by vol_{t-1}. Asymptotic p-values are in parentheses.

[a] Under the null, distributed as $\chi(3)$. The 5 percent critical value is 7.81.

volatility and volume may be simultaneously determined by the rate of information arrival. Therefore, the modified GARCH(1,1) model is reestimated with lagged values of volume (vol_{t-1}). The results, which are reported in Panel C, confirm the existence of a simultaneity problem. Lagged volume is significant only for the pre-crisis period. Compared to the coefficient estimates in Panel A, the results suggest that the inclusion of volume does not reduce the GARCH effects. Therefore, the analysis in this section provides only weak support to the hypothesis that volume has an impact on conditional return variance.

Conclusions

Provision of liquidity during crisis periods can be especially troublesome for emerging markets. This paper uses such a period, which can be attributed to the financial market crash in Russia, to examine the performance of the ISE. The unique data set in this paper is used to examine the contemporaneous relation between trading volume and return. The comparison of the relationship during the crisis period to the relationship during pre- and post-crisis periods shows that there was a structural change regarding the price impact of trading volume. The evidence indicates that traders needed to give considerably larger price concessions during the crisis period. The structural change was transitory since the cost of getting liquidity is shown to fall back during the post-crisis period. To give further insight on the return–volume relationship, the examination of conditional return variance during the three subperiods in the sample shows the following evidence: GARCH specification provides a good fit for the pre- and post-, but not for the crisis period. One possible explanation for this result may be that there was a considerable increase in leptokurtosis during the crisis period. Moreover, there is only weak evidence that volume explains conditional variance during the noncrisis periods.

Notes

1. See the survey article by Karpoff (1987) for a list of empirical works.
2. An organized securities market in Turkey has roots in the second half of the nineteenth century. Following the Crimean War, the first such market in the Ottoman Empire was established in 1866.
3. Split and dividend adjustments were performed for each stock.
4. To eliminate measurement error, the six days with fewer than sixteen intervals were excluded, which leaves 277 trading days and 4,432 intervals in the final sample.
5. For example, Akgiray (1989) and Lamoureux and Lastrapes (1990a, 1990b) are three studies that use GARCH(1,1) to characterize conditional variance of stock index and individual stock return time series.
6. Newey-West estimator of the covariance matrix of the least squares estimator is:

$$S = S_0 + \frac{1}{T}\sum_{\ell=1}^{L}\sum_{i=\ell+1}^{T} w(\ell) e_i e_{i-\ell}\left[x_i x'_{i-\ell} + x_{i-\ell} x'_i\right],$$

where

$$S_0 = \frac{1}{T}\sum_{i=1}^{T} e_i^2 x_i x_i'$$

and

$$w(\ell) = 1 - \frac{\ell}{L+1},$$

e_i is the least squares residual and autocorrelations greater than L are small enough to ignore.

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